03 Amazon Fine Food Reviews Analysis_KNN

May 7, 2019

1 Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective: Given a review, determine whether the review is positive (rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative? [Ans] We could use Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

2 [1]. Reading Data

2.1 [1.1] Loading the data

The dataset is available in two forms 1. .csv file 2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it is easier to query the data and visualise the data efficiently.

Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [28]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os
```

In [74]:
```
# using SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 data poin
# you can change the number to any other number based on your computing power

# taking 150K points for KNN in Descending Time Order
```

```
# Ascending Time order causes problem as the oldest data is 20 years old (dated 1999)
# data. Instead we will swap the train and test split in the code down the line so th
# data.

# 150000 data points were used for brute force KNN
#filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 ORDER B

# reducing the dataset size for kd-tree to 10000 to reduce the time taken
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 ORDER BY

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a negati
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(5)
```

Number of data points in our data (50000, 10)

Out[74]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	\
0	10	B00171APVA	A21BT40VZCCYT4	Carol A. Reed	0	
1	1089	B004FD13RW	A1BPLP0BKERV	Paul	0	
2	5703	B009WSNWC4	AMP7K1O84DH1T	ESTY	0	
3	5924	B00523NRVO	A2JDXKFZ0PFHKU	James W. Shondel	0	
4	7178	B0040QLIHK	AKHQMSUORSA91	Pen Name	0	

	HelpfulnessDenominator	Score	Time	Summary	\
0	0	1	1351209600	Healthy Dog Food	
1	0	1	1351209600	It is awesome.	
2	0	1	1351209600	DELICIOUS	
3	0	1	1351209600	The perfect pop!	
4	0	1	1351209600	Delicious!	

	Text
0	This is a very healthy dog food. Good for thei...
1	My partner is very happy with the tea, and is ...
2	Purchased this product at a local store in NY ...
3	These lollipops are are well done, look exactl...
4	I have ordered these raisins multiple times. ...

In [75]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
```

```
        FROM Reviews
        GROUP BY UserId
        HAVING COUNT(*)>1
        """, con)
```

```
In [76]: print(display.shape)
         display.head()
```

```
(80668, 7)
```

```
Out[76]:                UserId   ProductId             ProfileName        Time  Score  \
         0  #oc-R115TNMSPFT9I7  B007Y59HVM                 Breyton  1331510400      2
         1  #oc-R11D9D7SHXIJB9  B005HG9ET0  Louis E. Emory "hoppy"  1342396800      5
         2  #oc-R11DNU2NBKQ23Z  B007Y59HVM         Kim Cieszykowski  1348531200      1
         3  #oc-R11O5J5ZVQE25C  B005HG9ET0            Penguin Chick  1346889600      5
         4  #oc-R12KPBODL2B5ZD  B007OSBE1U   Christopher P. Presta  1348617600      1

                                                         Text  COUNT(*)
         0  Overall its just OK when considering the price...         2
         1  My wife has recurring extreme muscle spasms, u...         3
         2  This coffee is horrible and unfortunately not ...         2
         3  This will be the bottle that you grab from the...         3
         4  I didnt like this coffee. Instead of telling y...         2
```

```
In [77]: display[display['UserId']=='AZY10LLTJ71NX']
```

```
Out[77]:              UserId   ProductId                     ProfileName        Time  \
         80638  AZY10LLTJ71NX  B006P7E5ZI  undertheshrine "undertheshrine"  1334707200

                Score                                              Text  COUNT(*)
         80638      5  I was recommended to try green tea extract to ...         5
```

```
In [78]: display['COUNT(*)'].sum()
```

```
Out[78]: 393063
```

3 [2] Exploratory Data Analysis

3.1 [2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

```
In [79]: display= pd.read_sql_query("""
         SELECT *
         FROM Reviews
         WHERE Score != 3 AND UserId="AR5J8UI46CURR"
```

```
ORDER BY ProductID
""", con)
display.head()
```

```
Out[79]:        Id   ProductId         UserId      ProfileName  HelpfulnessNumerator  \
         0   78445  B000HDL1RQ  AR5J8UI46CURR  Geetha Krishnan                     2
         1  138317  B000HDOPYC  AR5J8UI46CURR  Geetha Krishnan                     2
         2  138277  B000HDOPYM  AR5J8UI46CURR  Geetha Krishnan                     2
         3   73791  B000HDOPZG  AR5J8UI46CURR  Geetha Krishnan                     2
         4  155049  B000PAQ75C  AR5J8UI46CURR  Geetha Krishnan                     2

            HelpfulnessDenominator  Score        Time  \
         0                       2      5  1199577600
         1                       2      5  1199577600
         2                       2      5  1199577600
         3                       2      5  1199577600
         4                       2      5  1199577600

                                 Summary  \
         0  LOACKER QUADRATINI VANILLA WAFERS
         1  LOACKER QUADRATINI VANILLA WAFERS
         2  LOACKER QUADRATINI VANILLA WAFERS
         3  LOACKER QUADRATINI VANILLA WAFERS
         4  LOACKER QUADRATINI VANILLA WAFERS

                                                  Text
         0  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
         1  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
         2  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
         3  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
         4  DELICIOUS WAFERS. I FIND THAT EUROPEAN WAFERS ...
```

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8) ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

```
In [80]: #Sorting data according to ProductId in ascending order
         sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fa
```

```
In [81]: #Deduplication of entries
         final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
         final.shape
```

```
Out[81]: (35610, 10)
```

```
In [82]: #Checking to see how much % of data still remains
         (final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100
```

```
Out[82]: 71.22
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

```
In [83]: display= pd.read_sql_query("""
         SELECT *
         FROM Reviews
         WHERE Score != 3 AND Id=44737 OR Id=64422
         ORDER BY ProductID
         """, con)

         display.head()
```

```
Out[83]:       Id   ProductId          UserId             ProfileName  \
         0  64422  B000MIDROQ  A161DK06JJMCYF  J. E. Stephens "Jeanne"
         1  44737  B001EQ55RW  A2V0I904FH7ABY                     Ram

            HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
         0                     3                       1      5  1224892800
         1                     3                       2      4  1212883200

                                             Summary  \
         0            Bought This for My Son at College
         1  Pure cocoa taste with crunchy almonds inside

                                                        Text
         0  My son loves spaghetti so I didn't hesitate or...
         1  It was almost a 'love at first bite' - the per...
```

```
In [84]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [85]: #Before starting the next phase of preprocessing lets see the number of entries left
         print(final.shape)

         #How many positive and negative reviews are present in our dataset?
         final['Score'].value_counts()
```

```
(35610, 10)
```

```
Out[85]: 1    29450
         0     6160
         Name: Score, dtype: int64
```

4 [3] Preprocessing

4.1 [3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

```
In [86]: # printing some random reviews
         sent_0 = final['Text'].values[0]
         print(sent_0)
         print("="*50)

         sent_1000 = final['Text'].values[1000]
         print(sent_1000)
         print("="*50)

         sent_1500 = final['Text'].values[1500]
         print(sent_1500)
         print("="*50)

         sent_4900 = final['Text'].values[4900]
         print(sent_4900)
         print("="*50)
```

```
TITLE: Chicken Soup with Rice<br />AUTHOR: Maurice Sendak<br />REVIEWER: Josh Grossman, Colonel
==================================================
Good product.  Easily fits inside golf bag.  Will keep your beer cold the entire round.  With r
==================================================
The product is what it advertise to be. If you expect it to taste as fresh eggs you will be dis
==================================================
I started buying these at my local CostCo and when Costco stopped carrying them I started buyin
==================================================
```

```
In [87]: # remove urls from text python: https://stackoverflow.com/a/40823105/4084039
         sent_0 = re.sub(r"http\S+", "", sent_0)
         sent_1000 = re.sub(r"http\S+", "", sent_1000)
         sent_150 = re.sub(r"http\S+", "", sent_1500)
         sent_4900 = re.sub(r"http\S+", "", sent_4900)

         print(sent_0)
```

```
TITLE: Chicken Soup with Rice<br />AUTHOR: Maurice Sendak<br />REVIEWER: Josh Grossman, Colonel
```

```
In [88]: # https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-remove-all
         from bs4 import BeautifulSoup

         soup = BeautifulSoup(sent_0, 'lxml')
         text = soup.get_text()
         print(text)
         print("="*50)

         soup = BeautifulSoup(sent_1000, 'lxml')
         text = soup.get_text()
         print(text)
         print("="*50)

         soup = BeautifulSoup(sent_1500, 'lxml')
         text = soup.get_text()
         print(text)
         print("="*50)

         soup = BeautifulSoup(sent_4900, 'lxml')
         text = soup.get_text()
         print(text)
```

```
TITLE: Chicken Soup with RiceAUTHOR: Maurice SendakREVIEWER: Josh Grossman, Colonel {r}, U.S.A
==================================================
Good product.  Easily fits inside golf bag.  Will keep your beer cold the entire round.  With m
==================================================
The product is what it advertise to be. If you expect it to taste as fresh eggs you will be dis
==================================================
I started buying these at my local CostCo and when Costco stopped carrying them I started buyin
```

```
In [89]: # https://stackoverflow.com/a/47091490/4084039
         import re

         def decontracted(phrase):
             # specific
             phrase = re.sub(r"won't", "will not", phrase)
             phrase = re.sub(r"can\'t", "can not", phrase)
```

```
    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

```
In [90]: sent_1500 = decontracted(sent_1500)
         print(sent_1500)
         print("="*50)
```

```
The product is what it advertise to be. If you expect it to taste as fresh eggs you will be di
==================================================
```

```
In [91]: #remove words with numbers python: https://stackoverflow.com/a/18082370/4084039
         sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
         print(sent_0)
```

```
TITLE: Chicken Soup with Rice<br />AUTHOR: Maurice Sendak<br />REVIEWER: Josh Grossman, Colone
```

```
In [92]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
         sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
         print(sent_1500)
```

```
The product is what it advertise to be If you expect it to taste as fresh eggs you will be dis
```

```
In [93]: # https://gist.github.com/sebleier/554280
         # we are removing the words from the stop words list: 'no', 'nor', 'not'
         # <br /><br /> ==> after the above steps, we are getting "br br"
         # we are including them into stop words list
         # instead of <br /> if we have <br/> these tags would have revmoved in the 1st step

         stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselv
                     "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him'
                     'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself',
                     'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "
                     'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', '
                     'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'a
                     'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'throug
                     'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', '
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'a
```

```
                'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too
                's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'n
                've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't"
                "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mig
                "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't",
                'won', "won't", 'wouldn', "wouldn't"])
```

```
In [94]: # Combining all the above stundents
         from tqdm import tqdm
         preprocessed_reviews = []
         # tqdm is for printing the status bar
         for sentance in tqdm(final['Text'].values):
             sentance = re.sub(r"http\S+", "", sentance)
             sentance = BeautifulSoup(sentance, 'lxml').get_text()
             sentance = decontracted(sentance)
             sentance = re.sub("\S*\d\S*", "", sentance).strip()
             sentance = re.sub('[^A-Za-z]+', ' ', sentance)
             # https://gist.github.com/sebleier/554280
             sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not in stopwo
             preprocessed_reviews.append(sentance.strip())
```

```
100%|| 35610/35610 [00:13<00:00, 2597.24it/s]
```

```
In [95]: print(preprocessed_reviews[100])
         print(len(preprocessed_reviews))
```

```
used brand years feeling clogged ate massive meal sips tea new make sure home work little well
35610
```

[3.2] Preprocessing Review Summary

```
In [96]: ## Similartly you can do preprocessing for review summary also.
```

5 [4] Featurization

5.1 [4.1] BAG OF WORDS

```
In [25]: #BoW
         count_vect = CountVectorizer() #in scikit-learn
         count_vect.fit(preprocessed_reviews)
         print("some feature names ", count_vect.get_feature_names()[:10])
         print('='*50)

         final_counts = count_vect.transform(preprocessed_reviews)
         print("the type of count vectorizer ",type(final_counts))
         print("the shape of out text BOW vectorizer ",final_counts.get_shape())
         print("the number of unique words ", final_counts.get_shape()[1])
```

```
some feature names  ['aa', 'aahhhs', 'aback', 'abandon', 'abates', 'abbott', 'abby', 'abdomina
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 12997)
the number of unique words  12997
```

5.2 [4.2] Bi-Grams and n-Grams.

In [26]:
```
#bi-gram, tri-gram and n-gram

#removing stop words like "not" should be avoided before building n-grams
# count_vect = CountVectorizer(ngram_range=(1,2))
# please do read the CountVectorizer documentation http://scikit-learn.org/stable/mod

# you can choose these numebrs min_df=10, max_features=5000, of your choice
count_vect = CountVectorizer(ngram_range=(1,2), min_df=10, max_features=5000)
final_bigram_counts = count_vect.fit_transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_bigram_counts))
print("the shape of out text BOW vectorizer ",final_bigram_counts.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_bigram
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

5.3 [4.3] TF-IDF

In [27]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(preprocessed_reviews)
print("some sample features(unique words in the corpus)",tf_idf_vect.get_feature_name
print('='*50)

final_tf_idf = tf_idf_vect.transform(preprocessed_reviews)
print("the type of count vectorizer ",type(final_tf_idf))
print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
print("the number of unique words including both unigrams and bigrams ", final_tf_idf
```

```
some sample features(unique words in the corpus) ['ability', 'able', 'able find', 'able get',
==================================================
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer  (4986, 3144)
the number of unique words including both unigrams and bigrams  3144
```

5.4 [4.4] Word2Vec

In [28]:
```
# Train your own Word2Vec model using your own text corpus
i=0
list_of_sentance=[]
for sentance in preprocessed_reviews:
    list_of_sentance.append(sentance.split())
```

In [42]:
```
# Using Google News Word2Vectors

# in this project we are using a pretrained model by google
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.


# http://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/#.W17SRFAzZPY
# you can comment this whole cell
# or change these varible according to your need

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    print(w2v_model.wv.most_similar('great'))
    print('='*50)
    print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bi
        print(w2v_model.wv.most_similar('great'))
        print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v = True, 
```

```
[('snack', 0.9951335191726685), ('calorie', 0.9946465492248535), ('wonderful', 0.99460321664810
==================================================
[('varieties', 0.9994194507598877), ('become', 0.9992934465408325), ('popcorn', 0.999275088310
```

In [36]:
```
w2v_words = list(w2v_model.wv.vocab)
```

```
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  3817
sample words  ['product', 'available', 'course', 'total', 'pretty', 'stinky', 'right', 'nearby
```

5.5 [4.4.1] Converting text into vectors using Avg W2V, TFIDF-W2V

[4.4.1.1] Avg W2v

```
In [38]: # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
         for sent in tqdm(list_of_sentance): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might need t
             cnt_words =0; # num of words with a valid vector in the sentence/review
             for word in sent: # for each word in a review/sentence
                 if word in w2v_words:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
             if cnt_words != 0:
                 sent_vec /= cnt_words
             sent_vectors.append(sent_vec)
         print(len(sent_vectors))
         print(len(sent_vectors[0]))
```

```
100%|| 4986/4986 [00:03<00:00, 1330.47it/s]


4986
50
```

[4.4.1.2] TFIDF weighted W2v

```
In [39]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
         model = TfidfVectorizer()
         tf_idf_matrix = model.fit_transform(preprocessed_reviews)
         # we are converting a dictionary with word as a key, and the idf as a value
         dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

```
In [41]: # TF-IDF weighted Word2Vec
         tfidf_feat = model.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

         tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this l
         row=0;
```

```
    for sent in tqdm(list_of_sentance): # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in w2v_words and word in tfidf_feat:
                vec = w2v_model.wv[word]
#                 tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                # to reduce the computation we are
                # dictionary[word] = idf value of word in whole courpus
                # sent.count(word) = tf valeus of word in this review
                tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
```

```
100%|| 4986/4986 [00:20<00:00, 245.63it/s]
```

6 [5] Assignment 3: KNN

```
<li><strong>Apply Knn(brute force version) on these feature sets</strong>
    <ul>
        <li><font color='red'>SET 1:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 2:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
    </ul>
</li>
<br>
<li><strong>Apply Knn(kd tree version) on these feature sets</strong>
    <br><font color='red'>NOTE: </font>sklearn implementation of kd-tree accepts only dense ma
    <ul>
        <li><font color='red'>SET 5:</font>Review text, preprocessed one converted into vectors
        <pre>
        count_vect = CountVectorizer(min_df=10, max_features=500)
        count_vect.fit(preprocessed_reviews)
        </pre>
        </li>
        <li><font color='red'>SET 6:</font>Review text, preprocessed one converted into vectors
        <pre>
            tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
            tf_idf_vect.fit(preprocessed_reviews)
        </pre>
        </li>
```

```
        <li><font color='red'>SET 3:</font>Review text, preprocessed one converted into vectors
        <li><font color='red'>SET 4:</font>Review text, preprocessed one converted into vectors
    </ul>
</li>
<br>
<li><strong>The hyper paramter tuning(find best K)</strong>
    <ul>
<li>Find the best hyper parameter which will give the maximum <a href='https://www.appliedaicou
<li>Find the best hyper paramter using k-fold cross validation or simple cross validation data
<li>Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this ta
    </ul>
</li>
<br>
<li>
<strong>Representation of results</strong>
    <ul>
<li>You need to plot the performance of model both on train data and cross validation data for
<img src='train_cv_auc.JPG' width=300px></li>
<li>Once after you found the best hyper parameter, you need to train your model with it, and fi
<img src='train_test_auc.JPG' width=300px></li>
<li>Along with plotting ROC curve, you need to print the <a href='https://www.appliedaicourse.c
<img src='confusion_matrix.png' width=300px></li>
    </ul>
</li>
<br>
<li><strong>Conclusion</strong>
    <ul>
<li>You need to summarize the results at the end of the notebook, summarize it in the table fo
    <img src='summary.JPG' width=400px>
</li>
    </ul>
```

Note: Data Leakage

1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
4. For more details please go through this link.

6.1 [5.1] Applying KNN brute force

In [97]:
```python
Y = final['Score']
X = preprocessed_reviews
#make sure we have correct X and Y
print(Y.shape)
print(len(X))
```

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_tes
from sklearn.model_selection import train_test_split
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sk
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import confusion_matrix
from tqdm import tqdm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt


#  Train on oldest data (eg. Now - 90 days), CV on somewhat recent  data (eg. Now - 3
# doing a time series split:  swapped the test and train as our data is in DESCENDING
# and we want X_test to have the most recent data.
X_test, X_train, y_test, y_train = train_test_split(X, Y, test_size=0.77, shuffle=Fal

# time series splitting
X_cv, X_train, y_cv, y_train = train_test_split(X_train, y_train, test_size=0.77, shu
# do random between train and CV
#X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33)

print('X_train size=' , len(X_train))
print('X_cv size=', len(X_cv))
print('X_test size=', len(X_test))
print('y_train class counts')
print(y_train.value_counts())
print('y_cv class counts')
print(y_cv.value_counts())
print('y_test class counts')
print(y_test.value_counts())

#the following should all be the same.
#print(X_test[0])
#print(preprocessed_reviews[0])
#print(final['Text'].values[0])

K = [1, 5, 10, 15, 21, 31, 41, 51]

def computeWithBestK(best_k, xtrain, ytrain, xtest, ytest, algo):
    neigh = KNeighborsClassifier(n_neighbors=best_k, algorithm=algo)
    neigh.fit(xtrain, ytrain)
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimate
    # not the predicted outputs
    train_fpr, train_tpr, thresholds = roc_curve(ytrain, neigh.predict_proba(xtrain)[
    test_fpr, test_tpr, thresholds = roc_curve(ytest, neigh.predict_proba(xtest)[:,1]
    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
```

```
    plt.legend()
    plt.xlabel("K: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()
    print("="*100)

    print('y_train class counts')
    print(ytrain.value_counts())
    print('y_test class counts')
    print(ytest.value_counts())
    print("Train confusion matrix")
    print(confusion_matrix(ytrain, neigh.predict(xtrain)))
    print("Test confusion matrix")
    print(confusion_matrix(ytest, neigh.predict(xtest)))

def findBestK(X_train, y_train, X_cv, y_cv, kvalues, algo):
    """ y_true : array, shape = [n_samples] or [n_samples, n_classes]
    True binary labels or binary label indicators.
    y_score : array, shape = [n_samples] or [n_samples, n_classes]
    Target scores, can either be probability estimates of the positive class, confide
    decisions (as returned by decision_function on some classifiers).
    For binary y_true, y_score is supposed to be the score of the class with greater
    """
    train_auc = []
    cv_auc = []
    for i in tqdm(kvalues):
        neigh = KNeighborsClassifier(n_neighbors=i, algorithm=algo)
        neigh.fit(X_train, y_train)
        # roc_auc_score(y_true, y_score) the 2nd parameter should be probability esti
        # not the predicted outputs
        y_train_pred =  neigh.predict_proba(X_train)[:,1]
        y_cv_pred =  neigh.predict_proba(X_cv)[:,1]

        train_auc.append(roc_auc_score(y_train,y_train_pred))
        cv_auc.append(roc_auc_score(y_cv, y_cv_pred))

    plt.plot(kvalues, train_auc, label='Train AUC')
    plt.scatter(kvalues, train_auc, label='Train AUC')
    plt.plot(kvalues, cv_auc, label='CV AUC')
    plt.scatter(kvalues, cv_auc, label='CV AUC')
    plt.legend()
    plt.xlabel("K: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.show()
```

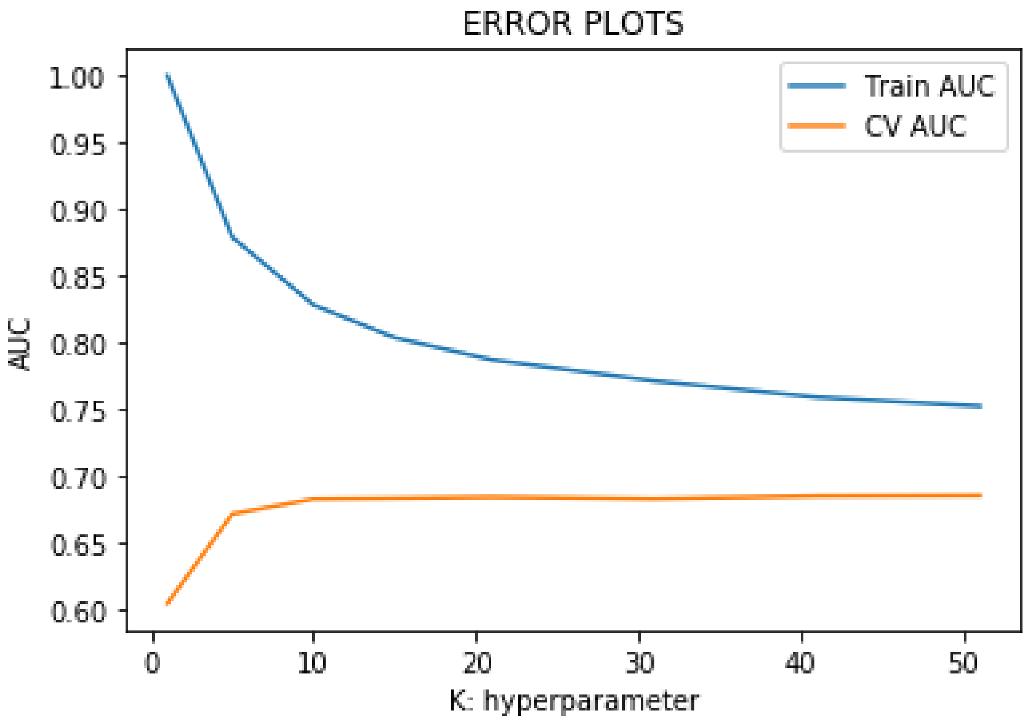
```
(35610,)
35610
X_train size= 21114
X_cv size= 6306
X_test size= 8190
y_train class counts
1    17598
0     3516
Name: Score, dtype: int64
y_cv class counts
1    5159
0    1147
Name: Score, dtype: int64
y_test class counts
1    6693
0    1497
Name: Score, dtype: int64
```

6.1.1 [5.1.1] Applying KNN brute force on BOW, SET 1

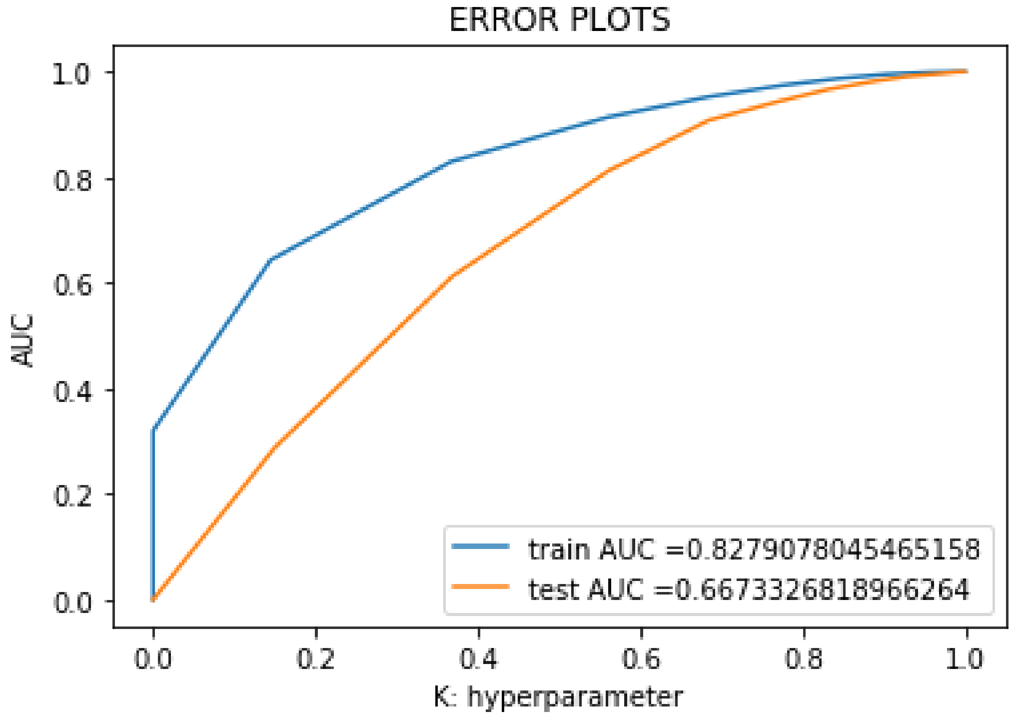
```
In [33]: from sklearn.feature_extraction.text import CountVectorizer

         # missed providing min_df
         vectorizer = CountVectorizer()

         # While vectorizing your data, apply the method fit_transform() on you train data,
         # and apply the method transform() on cv/test data.
         # THE VOCABULARY SHOULD BUILT ONLY WITH THE WORDS OF TRAIN DATA
         vectorizer.fit(X_train)

         # we use the fitted CountVectorizer to convert the text to vector
         X_train_bow = vectorizer.transform(X_train)
         X_cv_bow = vectorizer.transform(X_cv)
         X_test_bow = vectorizer.transform(X_test)

         print("After vectorizations")
         print(X_train_bow.shape, y_train.shape)
         print(X_cv_bow.shape, y_cv.shape)
         print(X_test_bow.shape, y_test.shape)
         print(type(X_train_bow))

         # this was run with 150k data points
         findBestK(X_train_bow, y_train, X_cv_bow, y_cv, K, 'brute')
```

```
  0%|          | 0/8 [00:00<?, ?it/s]
```

```
After vectorizations
(62558, 46863) (62558,)
(18686, 46863) (18686,)
(24267, 46863) (24267,)
<class 'scipy.sparse.csr.csr_matrix'>


100%|| 8/8 [34:58<00:00, 262.96s/it]
```



In [34]:
```
# best k seems to occur at 10 on the CV data
bestk = 10
computeWithBestK(bestk, X_train_bow, y_train, X_test_bow, y_test, 'brute')
```



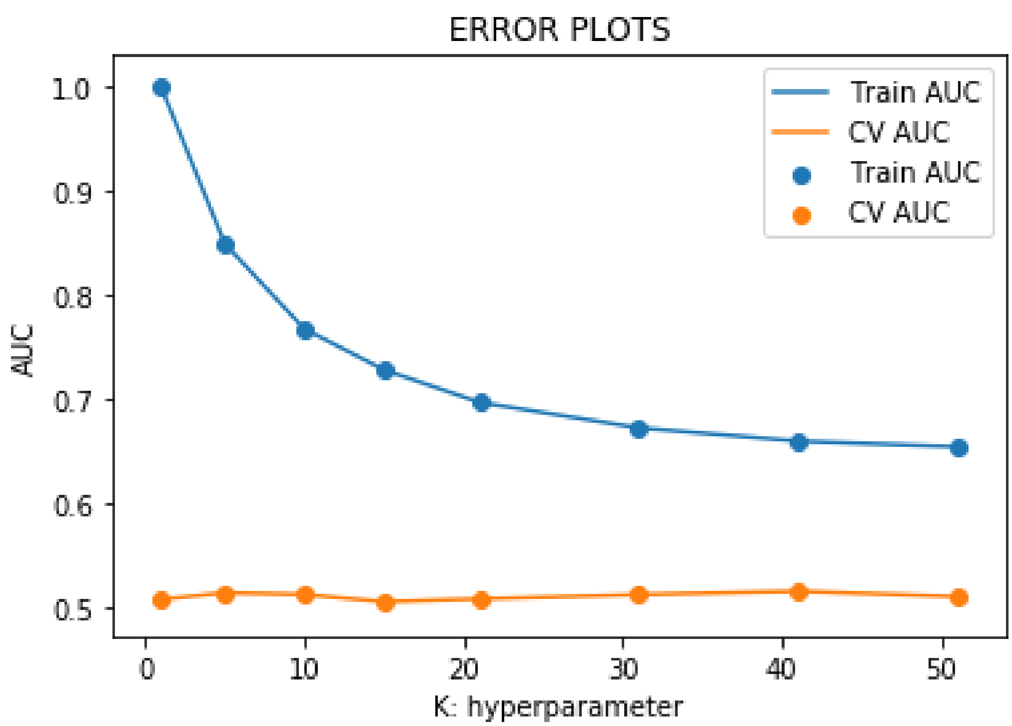

```
====================================================================================================
Train confusion matrix
[[ 3330  7171]
 [ 2499 49558]]
Test confusion matrix
[[ 1026  3466]
 [ 1107 18668]]
```

6.1.2 [5.1.2] Applying KNN brute force on TFIDF, SET 2

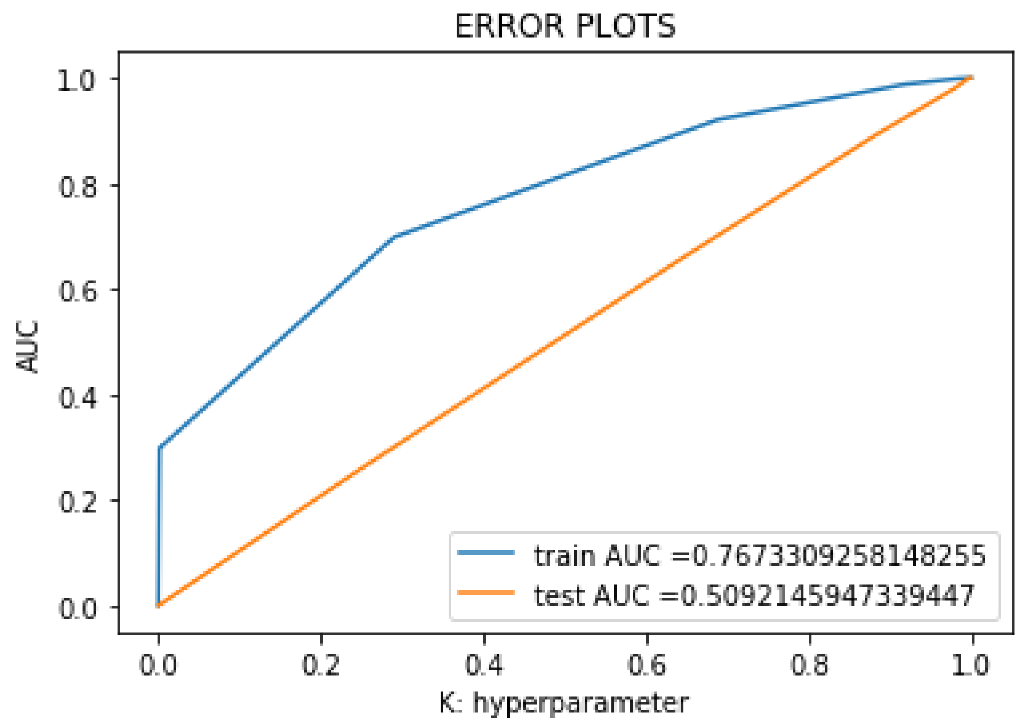
```
In [60]: from sklearn.feature_extraction.text import TfidfTransformer
         from sklearn.feature_extraction.text import TfidfVectorizer
         from tqdm import tqdm
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.metrics import roc_auc_score
         import matplotlib.pyplot as plt


         vectorizer = TfidfVectorizer(ngram_range=(1,2), min_df=10)
         vectorizer.fit(X_train)

         # we use the fitted vectorizer to convert the text to vector
         X_train_tfidf = vectorizer.transform(X_train)
```

```
X_cv_tfidf = vectorizer.transform(X_cv)
X_test_tfidf = vectorizer.transform(X_test)

print("After vectorizations")
print(X_train_tfidf.shape, y_train.shape)
print(X_cv_tfidf.shape, y_cv.shape)
print(X_test_tfidf.shape, y_test.shape)

print(type(X_train_tfidf))

# this was run with 150k data points
findBestK(X_train_tfidf, y_train, X_cv_tfidf, y_cv, K, 'brute')
```

```
  0%|          | 0/8 [00:00<?, ?it/s]

After vectorizations
(62558, 38031) (62558,)
(18686, 38031) (18686,)
(24267, 38031) (24267,)
<class 'scipy.sparse.csr.csr_matrix'>


100%|| 8/8 [39:00<00:00, 296.53s/it]
```



In [61]:
```
#for TFIDF the best score seems to be around K=40 however overall the AUC seems to in
bestk = 10
computeWithBestK(bestk, X_train_tfidf, y_train, X_test_tfidf, y_test, 'brute')
```




```
==========================================================================================
Train confusion matrix
[[  163 10338]
 [   53 52004]]
Test confusion matrix
[[   22  4470]
 [   55 19720]]
```

6.1.3 [5.1.3] Applying KNN brute force on AVG W2V, SET 3

In [98]:
```
from gensim.models import Word2Vec
from gensim.models import KeyedVectors


def computeAvgW2V(X):
    list_of_sentence_train=[]
    for sentence in X:
        list_of_sentence_train.append(sentence.split())
```

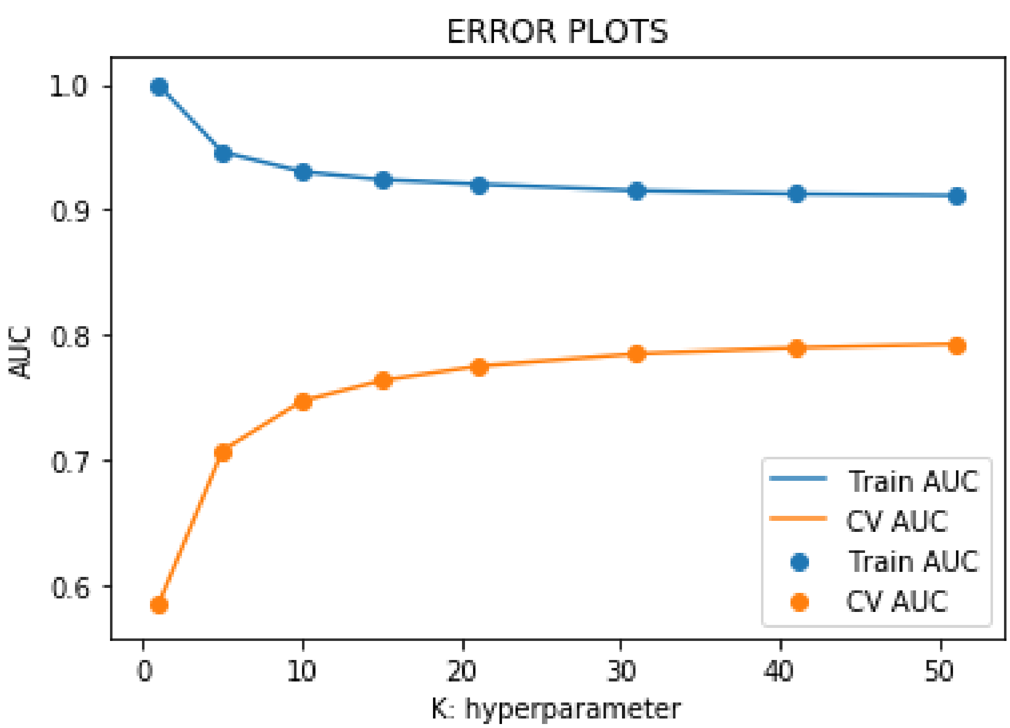
```
        # this line of code trains your w2v model on the give list of sentances
        w2v_model=Word2Vec(list_of_sentence_train,min_count=5,size=50, workers=4)
        w2v_words = list(w2v_model.wv.vocab)

        # average Word2Vec
        # compute average word2vec for each review.
        sent_vectors_train = [] # the avg-w2v for each sentence/review is stored in this
        for sent in tqdm(list_of_sentence_train): # for each review/sentence
            sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might ne
            cnt_words =0; # num of words with a valid vector in the sentence/review
            for word in sent: # for each word in a review/sentence
                if word in w2v_words:
                    vec = w2v_model.wv[word]
                    sent_vec += vec
                    cnt_words += 1
            if cnt_words != 0:
                sent_vec /= cnt_words
            sent_vectors_train.append(sent_vec)
        sent_vectors_train = np.array(sent_vectors_train)
        print(sent_vectors_train.shape)
        print(sent_vectors_train[0])
        return sent_vectors_train
```

In [62]:
```
# this was run with 150K data points
X_train_w2vAvg = computeAvgW2V(X_train)
X_cv_w2vAvg = computeAvgW2V(X_cv)

findBestK(X_train_w2vAvg, y_train, X_cv_w2vAvg, y_cv, K, 'brute')
```

```
100%|| 62558/62558 [02:21<00:00, 443.52it/s]


(62558, 50)
[ 0.0956141  -0.09588509 -0.21131495 -0.18434832 -0.58558757 -0.10193755
 -0.42522606  0.19921311 -0.69575184 -0.5917278   0.79372043  0.1935179
 -0.38020522  0.80866488  0.68049298 -0.39613794 -0.39087397  0.16944171
 -0.46274642 -0.1873371  -0.30223544 -0.33656272  0.4065017   0.53915776
 -0.34389267  0.1857597   0.34048091  0.43953231 -0.10769706  0.26451289
 -0.91468374 -0.44146124  0.1677813   0.45220851 -0.65802206 -0.03871724
 -0.07974075  1.03034357 -0.43555852  1.04350169 -0.13713195 -0.24534033
  0.16508746 -0.28576288 -0.74990852  0.49749934  0.22049461 -0.71628084
 -0.17652292  0.2842603 ]


100%|| 18686/18686 [00:27<00:00, 667.63it/s]
  0%|          | 0/8 [00:00<?, ?it/s]

(18686, 50)
[ 1.84347679e-01 -6.58501434e-01  1.36849313e-01 -2.46733146e-01
```

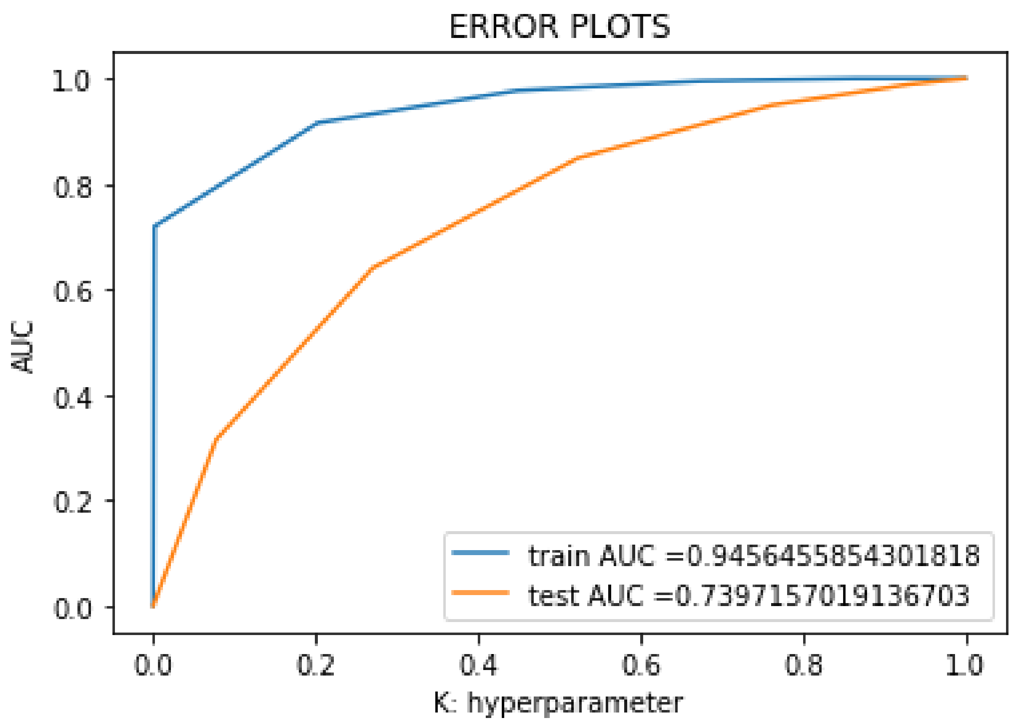
```
 5.73255095e-02 -8.34290719e-02  1.37296568e-01  5.43446057e-02
-8.41252110e-01 -1.27020178e-01  3.51006283e-02  2.99762840e-01
 1.52513715e-01  4.88177994e-02  3.78493757e-01  6.71850966e-01
 1.83237182e-01 -1.18276419e-01 -2.89755117e-01 -3.98465651e-01
 2.12517617e-01 -1.39784236e-01  1.88298603e-02  1.52307932e-01
-2.66843212e-01  1.88820348e-01 -2.90434748e-01  4.98956868e-05
 8.73898978e-01  6.26448446e-01 -1.63170435e-01  5.00768532e-02
-4.20777488e-01 -2.71910628e-01 -5.55161254e-01  1.03775605e-01
-3.15684538e-01  3.39466657e-01  3.10072006e-01  3.53257524e-01
 1.74011158e-01 -6.23381187e-01  2.46463701e-02 -1.86075083e-01
 3.10289115e-01  8.33608392e-03 -4.45910090e-01 -4.57401816e-01
-5.75374357e-01  3.39470379e-01]
```

```
100%|| 8/8 [16:49<00:00, 128.20s/it]
```



In [63]:
```
#bestK is at 50 on CV data
bestk = 50
# although bestk was at 50 the results below are run with bestk=5 by mistake.
# did not run it again with 50 just to save time
X_test_w2vAvg = computeAvgW2V(X_test)
computeWithBestK(bestk, X_train_w2vAvg, y_train, X_test_w2vAvg, y_test, 'brute')
```

```
100%|| 24267/24267 [00:42<00:00, 570.65it/s]


(24267, 50)
[ 0.05722205 -0.41714801 -0.18966312 -0.08203263  0.16622821 -0.73314584
  0.06638867  0.58827762 -0.66748154 -0.13053651  0.5681102   0.04000342
  0.35163522  0.43202972 -0.05652796 -0.21276995  0.3941835  -0.34050561
  0.00658449 -0.26944048  0.01840416  0.40283328  0.31930665 -0.26346477
  0.2911484  -0.06314379 -0.35490712 -0.1436747   0.412557    0.47062388
 -0.16643572  0.00966338  0.26763915 -0.20309302 -0.55375178  0.02616717
 -0.16545599 -0.03081029  0.6422904   0.72696385 -0.22275469 -0.39108401
 -0.42720607  0.77451868 -0.28802795 -0.17051758  0.53623273 -0.34965817
 -0.04232369  0.05083253]
```




```
==========================================================================
Train confusion matrix
[[ 5787  4714]
 [ 1186 50871]]
Test confusion matrix
[[ 2141  2351]
 [ 2983 16792]]
```

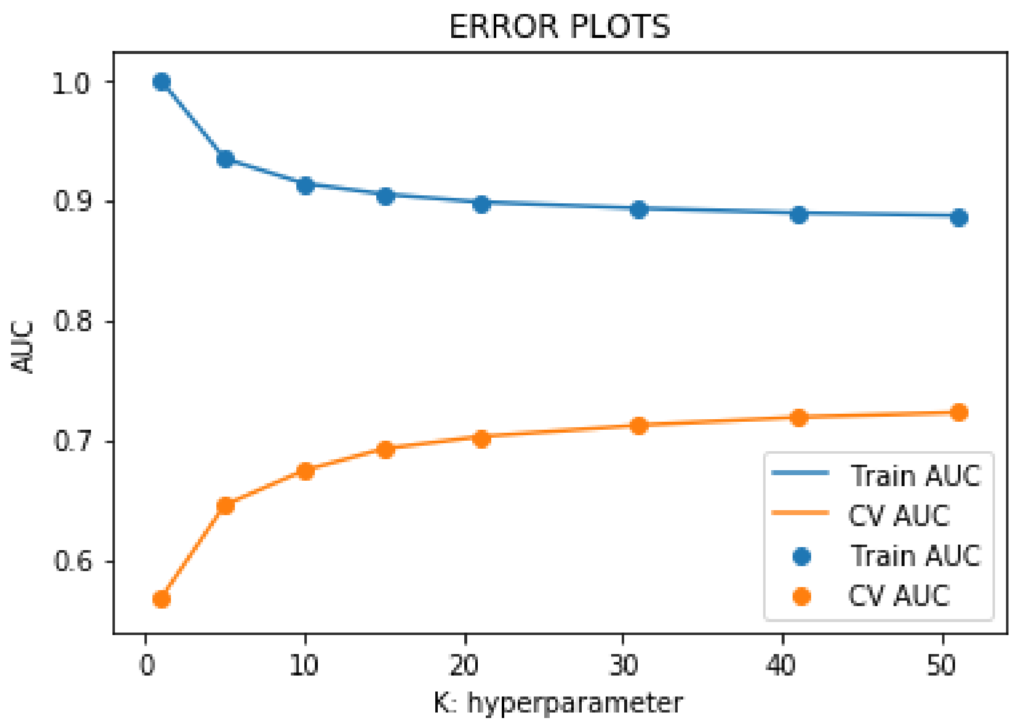
6.1.4 [5.1.4] Applying KNN brute force on TFIDF W2V, SET 4

```
In [99]: def computeTfIdfW2v(data):

             list_of_sentence_train=[]
             for sentence in data:
                 list_of_sentence_train.append(sentence.split())

             model = TfidfVectorizer(ngram_range=(1,2), min_df=10)
             model.fit(data)
             # we are converting a dictionary with word as a key, and the idf as a value
             dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))

              # this line of code trains your w2v model on the give list of sentances
             w2v_model=Word2Vec(list_of_sentence_train,min_count=5,size=50, workers=4)
             w2v_words = list(w2v_model.wv.vocab)

             # TF-IDF weighted Word2Vec
             tfidf_feat = model.get_feature_names() # tfidf words/col-names
             # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = t

             tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in th
             row=0;
             for sent in tqdm(list_of_sentence_train): # for each review/sentence
                 sent_vec = np.zeros(50) # as word vectors are of zero length
                 weight_sum =0; # num of words with a valid vector in the sentence/review
                 for word in sent: # for each word in a review/sentence
                     if word in w2v_words and word in tfidf_feat:
                         vec = w2v_model.wv[word]
                         #tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
                         # to reduce the computation we are
                         # dictionary[word] = idf value of word in whole courpus
                         # sent.count(word) = tf valeus of word in this review
                         tf_idf = dictionary[word]*(sent.count(word)/len(sent))
                         sent_vec += (vec * tf_idf)
                         weight_sum += tf_idf
                 if weight_sum != 0:
                     sent_vec /= weight_sum
                 tfidf_sent_vectors.append(sent_vec)
                 row += 1
             return tfidf_sent_vectors
```

```
In [25]: # this was run with 150k data points
         X_train_w2vTfIdf = computeTfIdfW2v(X_train)
         X_cv_w2vTfIdf = computeTfIdfW2v(X_cv)

         findBestK(X_train_w2vTfIdf, y_train, X_cv_w2vTfIdf, y_cv, K, 'brute')
```

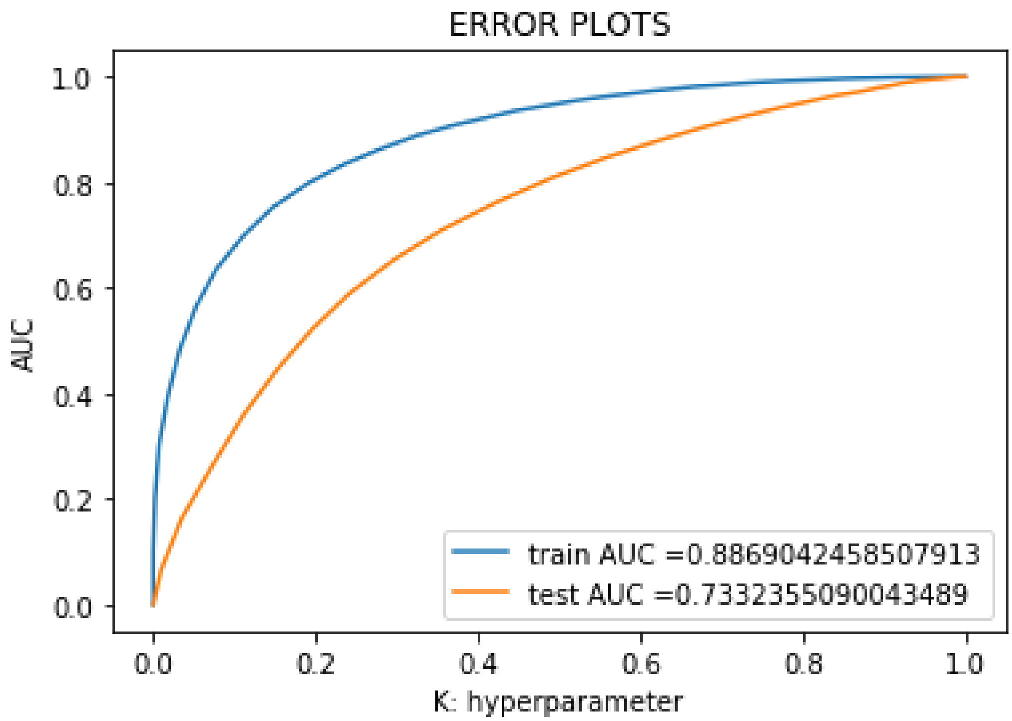
```
100%|| 62558/62558 [1:02:07<00:00, 16.78it/s]
```

```
100%|| 18686/18686 [03:25<00:00, 68.21it/s]
100%|| 8/8 [17:40<00:00, 133.55s/it]
```



In [26]:
```
#bestK is at 50 based on CV data
bestk = 50
X_test_w2vTfIdf = computeTfIdfW2v(X_test)
computeWithBestK(bestk, X_train_w2vTfIdf, y_train, X_test_w2vTfIdf, y_test, 'brute')
```

```
100%|| 24267/24267 [04:24<00:00, 91.88it/s]
```




```
==========================================================================================
y_train class counts
1    52057
0    10501
Name: Score, dtype: int64
y_test class counts
1    19775
0     4492
Name: Score, dtype: int64
Train confusion matrix
[[ 2950  7551]
 [  690 51367]]
Test confusion matrix
[[  205  4287]
 [  116 19659]]
```

6.2 [5.2] Applying KNN kd-tree

In [100]:
```
#4. You can use sparse matrices for brute force algorithm of KNN.
#5. For kd-tree algorithm you have to use dense matrices. Please note that if you pa
#6. Use AUC as a metric for hyperparameter tuning.

from sklearn.feature_extraction.text import CountVectorizer
```

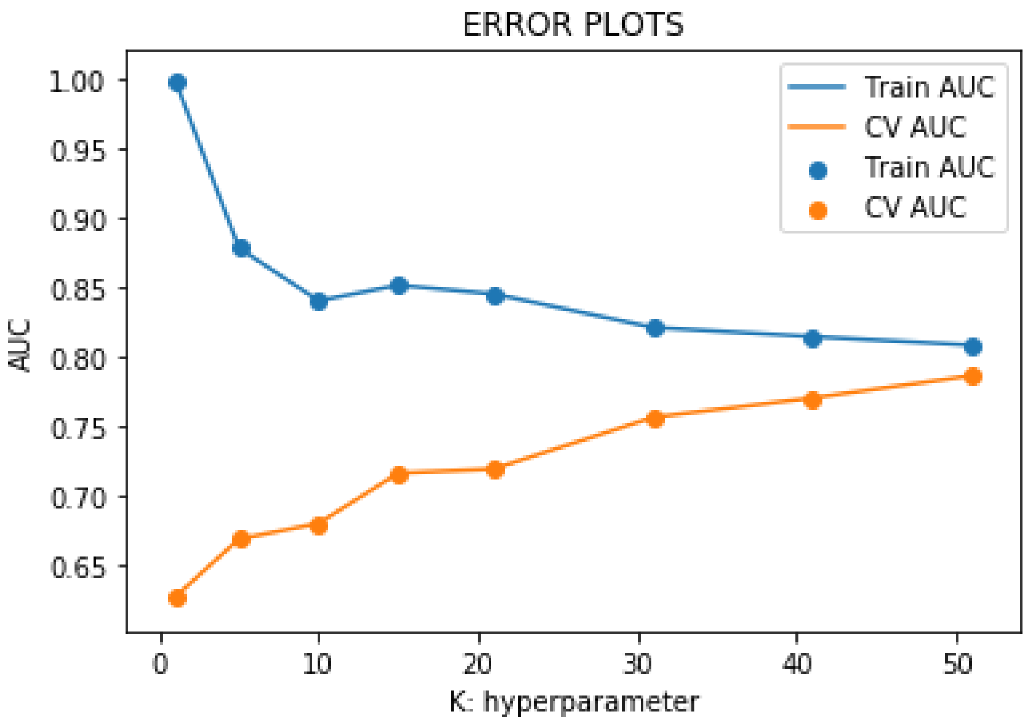
```
# missed providing min_df
vectorizer = CountVectorizer()

# While vectorizing your data, apply the method fit_transform() on you train data,
# and apply the method transform() on cv/test data.
# THE VOCABULARY SHOULD BUILT ONLY WITH THE WORDS OF TRAIN DATA
vectorizer.fit(X_train)

# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = vectorizer.transform(X_train)
X_cv_bow = vectorizer.transform(X_cv)
X_test_bow = vectorizer.transform(X_test)

print("After vectorizations")
print(X_train_bow.shape, y_train.shape)
print(X_cv_bow.shape, y_cv.shape)
print(X_test_bow.shape, y_test.shape)
print(type(X_train_bow))

X_train_bow_dense = X_train_bow.toarray()
X_cv_bow_dense = X_cv_bow.toarray()
X_test_bow_dense = X_test_bow.toarray()

print(type(X_train_bow_dense))
```

```
After vectorizations
(21114, 27249) (21114,)
(6306, 27249) (6306,)
(8190, 27249) (8190,)
<class 'scipy.sparse.csr.csr_matrix'>
<class 'numpy.ndarray'>
```

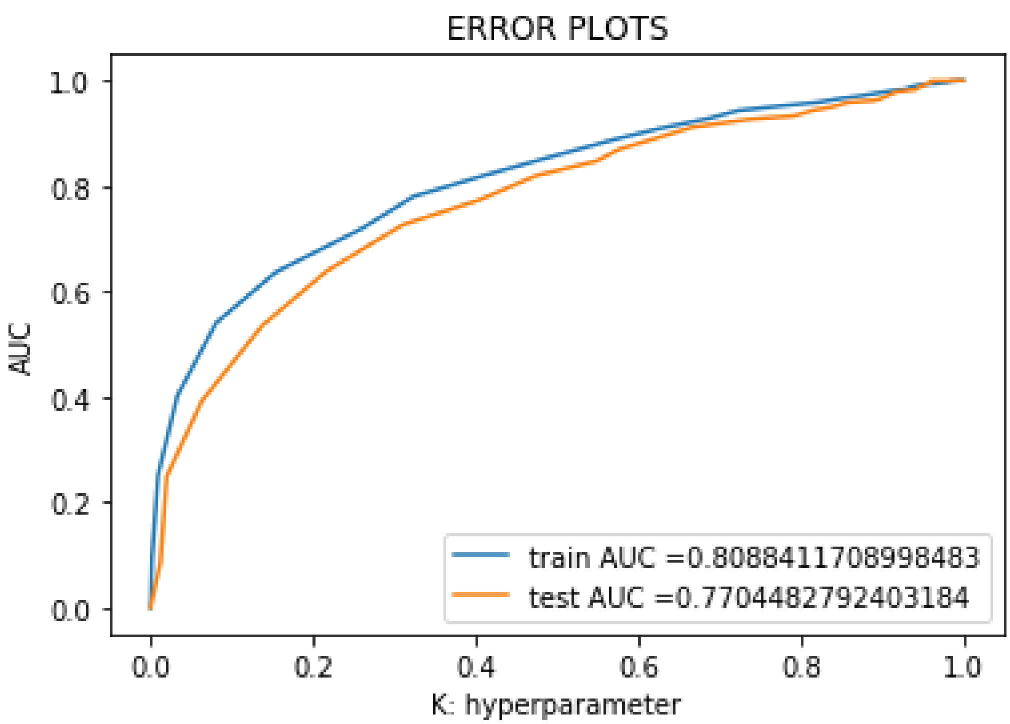
6.2.1 [5.2.1] Applying KNN kd-tree on BOW, SET 5

```
In [55]: # this was run with 10K data points only
         findBestK(X_train_bow_dense, y_train, X_cv_bow_dense, y_cv, K, 'kd_tree')
```

```
100%|| 8/8 [1:01:05<00:00, 490.03s/it]
```




```
In [56]: # best k seems to occur at 50 on the CV data
         bestk = 50
         computeWithBestK(bestk, X_train_bow_dense, y_train, X_test_bow_dense, y_test, 'kd_tree
```



```
==========================================================================================
y_train class counts
1    3599
0     671
Name: Score, dtype: int64
y_test class counts
1    1401
0     255
Name: Score, dtype: int64
Train confusion matrix
[[  37  634]
 [  32 3567]]
Test confusion matrix
[[  14  241]
 [  19 1382]]
```

6.2.2 [5.2.2] Applying KNN kd-tree on TFIDF, SET 6

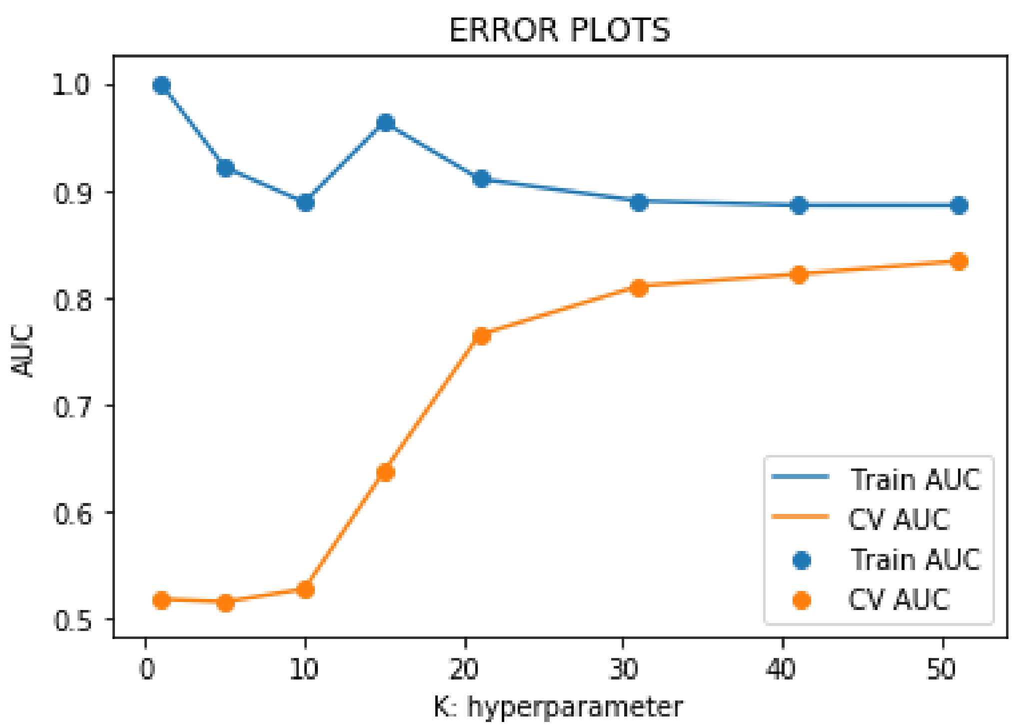
In [101]:
```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from tqdm import tqdm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt


vectorizer = TfidfVectorizer(ngram_range=(1,2), min_df=10)
vectorizer.fit(X_train)

# we use the fitted vectorizer to convert the text to vector
X_train_tfidf = vectorizer.transform(X_train)
X_cv_tfidf = vectorizer.transform(X_cv)
X_test_tfidf = vectorizer.transform(X_test)

print("After vectorizations")
print(X_train_tfidf.shape, y_train.shape)
print(X_cv_tfidf.shape, y_cv.shape)
print(X_test_tfidf.shape, y_test.shape)

print(type(X_train_tfidf))
X_train_tfidf_dense = X_train_tfidf.toarray()
X_cv_tfidf_dense = X_cv_tfidf.toarray()
X_test_tfidf_dense = X_test_tfidf.toarray()
```

```
print(type(x_train_tfidf_dense))
```

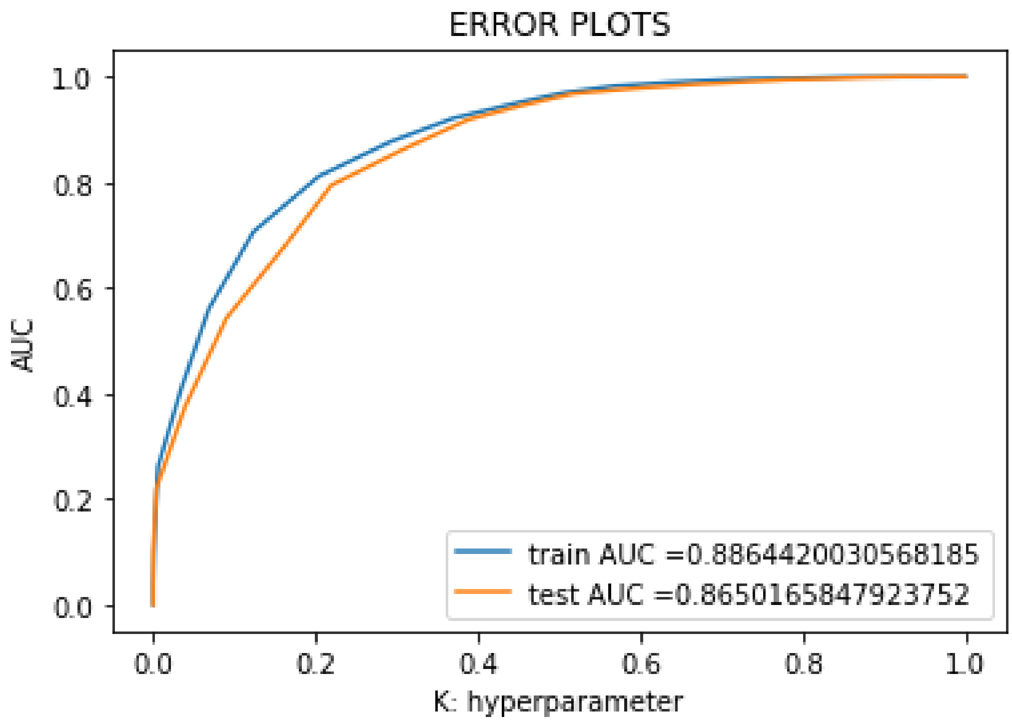
```
After vectorizations
(21114, 12239) (21114,)
(6306, 12239) (6306,)
(8190, 12239) (8190,)
<class 'scipy.sparse.csr.csr_matrix'>
<class 'numpy.ndarray'>
```

In [60]:
```
# this was run with 10K data points only
findBestK(X_train_tfidf_dense, y_train, X_cv_tfidf_dense, y_cv, K, 'kd_tree')
```

```
100%|| 8/8 [11:31<00:00, 94.22s/it]
```



In [61]:
```
#for TFIDF the best score seems to be around K=50
bestk = 50
computeWithBestK(bestk, X_train_tfidf_dense, y_train, X_test_tfidf_dense, y_test, 'kd_
```



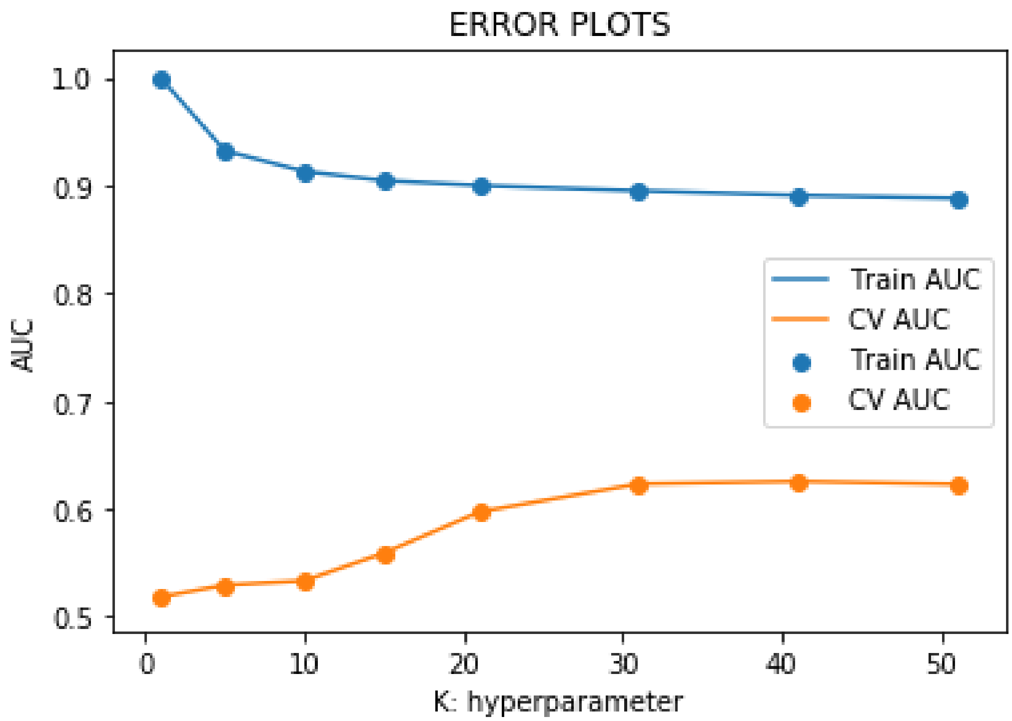

```
==========================================================================================
y_train class counts
1    3599
0     671
Name: Score, dtype: int64
y_test class counts
1    1401
0     255
Name: Score, dtype: int64
Train confusion matrix
[[  21  650]
 [   0 3599]]
Test confusion matrix
[[  10  245]
 [   0 1401]]
```

6.2.3 [5.2.3] Applying KNN kd-tree on AVG W2V, SET 3

In [102]:
```
# It was run with 50k data points
X_train_w2vAvg = computeAvgW2V(X_train)
X_cv_w2vAvg = computeAvgW2V(X_cv)

print(type(X_train_w2vAvg))
```

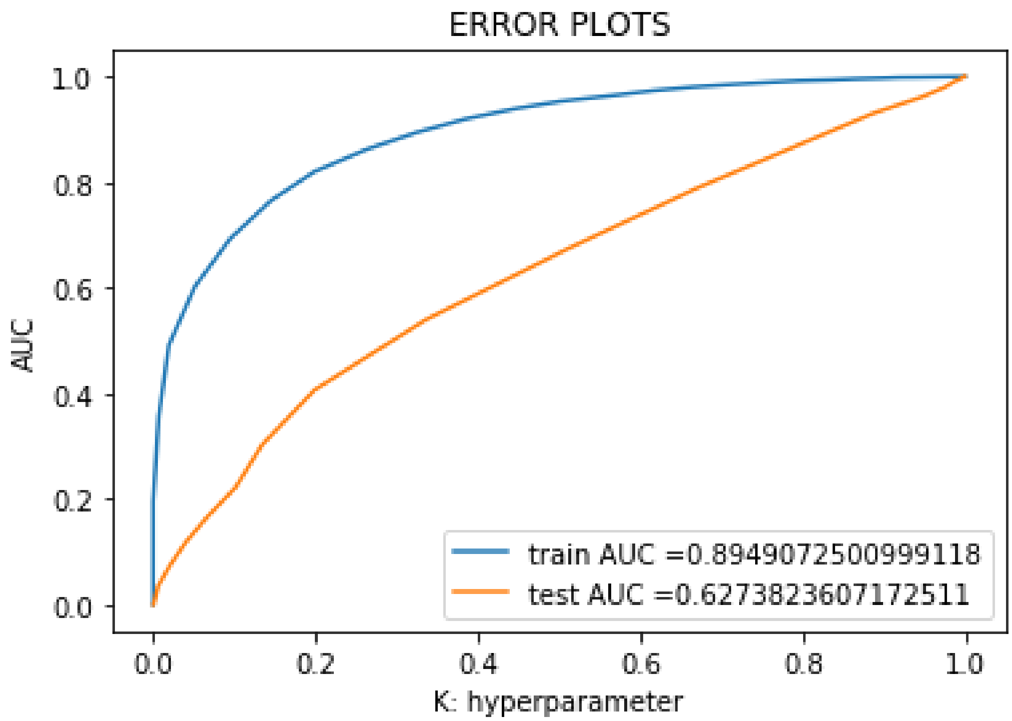
```python
print(type(X_cv_w2vAvg))

findBestK(X_train_w2vAvg, y_train, X_cv_w2vAvg, y_cv, K, 'kd_tree')
```

```
100%|| 21114/21114 [00:28<00:00, 738.36it/s]


(21114, 50)
[ 1.25908529e+00  4.10572452e-01 -8.09076403e-01  9.54783592e-02
  3.28209622e-02  5.18802607e-01  6.83745415e-01  5.32306341e-01
 -1.93320721e-01  6.21974414e-01 -3.45025818e-01 -6.22937619e-01
  5.71168449e-01  7.21171134e-01  4.86557345e-01 -3.87681841e-01
 -1.31058511e+00  4.26924680e-01  7.15454898e-01  2.79941679e-01
  4.91952234e-01  1.65232490e-01 -1.03346748e+00 -1.38395880e+00
  1.41190366e-01 -3.47602754e-01  4.66670138e-01 -1.59114514e-01
  4.03325406e-02  6.77252802e-02 -5.61399158e-01 -3.87223402e-01
 -8.61961528e-04 -5.66019220e-01  3.67728553e-01 -2.20084670e-01
 -6.50712494e-01 -1.10375483e+00 -1.38402218e-01 -9.25696494e-01
 -8.36431741e-01  3.43573263e-01 -1.53397782e-01 -2.59826729e-01
 -1.26759861e-01 -1.64110752e-01 -3.67073483e-01 -9.21212385e-01
  4.45883462e-01  2.07585444e-01]


100%|| 6306/6306 [00:05<00:00, 1075.74it/s]
  0%|          | 0/8 [00:00<?, ?it/s]

(6306, 50)
[ 0.26705551  0.35168104  0.25187186  0.0430147  -0.02583381  0.33161898
 -0.50528092 -0.02587186 -0.19294799  0.43141042 -0.18481261 -0.51981188
  0.62940413  0.33419473  0.06780154  0.52801859 -0.38311777  0.45969797
  0.59550995  0.34532699  0.08093421 -0.51470337 -0.28664636 -0.7965646
 -0.30221858 -0.21796107  0.23846154  0.45230556 -0.26127945  0.06468096
 -0.20360599  0.37730895 -0.34084673  0.28584874  0.00372759 -0.18513125
  0.22846525 -0.6047803   0.06799808 -0.35456591  0.30402802  0.07362201
 -0.00598939  0.03390868  0.31459739 -0.3197379  -0.5092181  -0.43591914
  0.11470002  0.37566399]
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>


100%|| 8/8 [09:39<00:00, 77.69s/it]
```



In [103]:
```
#bestK is at 31 on CV data
bestk = 31
X_test_w2vAvg = computeAvgW2V(X_test)
print(type(X_test_w2vAvg))
computeWithBestK(bestk, X_train_w2vAvg, y_train, X_test_w2vAvg, y_test, 'kd_tree')
```

```
100%|| 8190/8190 [00:09<00:00, 856.97it/s]


(8190, 50)
[ 0.44860686  0.27477915 -0.19504274  0.09698405 -0.17597843 -0.42791732
 -0.38134129 -0.07146016 -0.07493166  0.22351711 -0.76981997 -0.46618986
  0.30511611  0.16674421 -0.14384506  0.38216309 -0.40805017  0.24061763
  0.41436458  0.38952062  0.32029492 -0.52173317 -0.00874167 -0.32538948
 -0.01220131 -0.0694322   0.06055134  0.25427426  0.04759469  0.48229675
 -0.49692008  0.13124971 -0.16377191 -0.07779555 -0.28454058 -0.0057687
  0.2518219  -0.63968719 -0.07282865 -0.75786974  0.22974649  0.21738652
  0.24584965 -0.06774181 -0.0715845  -0.06536369  0.03057927 -0.38307962
  0.1422885   0.47200006]
<class 'numpy.ndarray'>
```



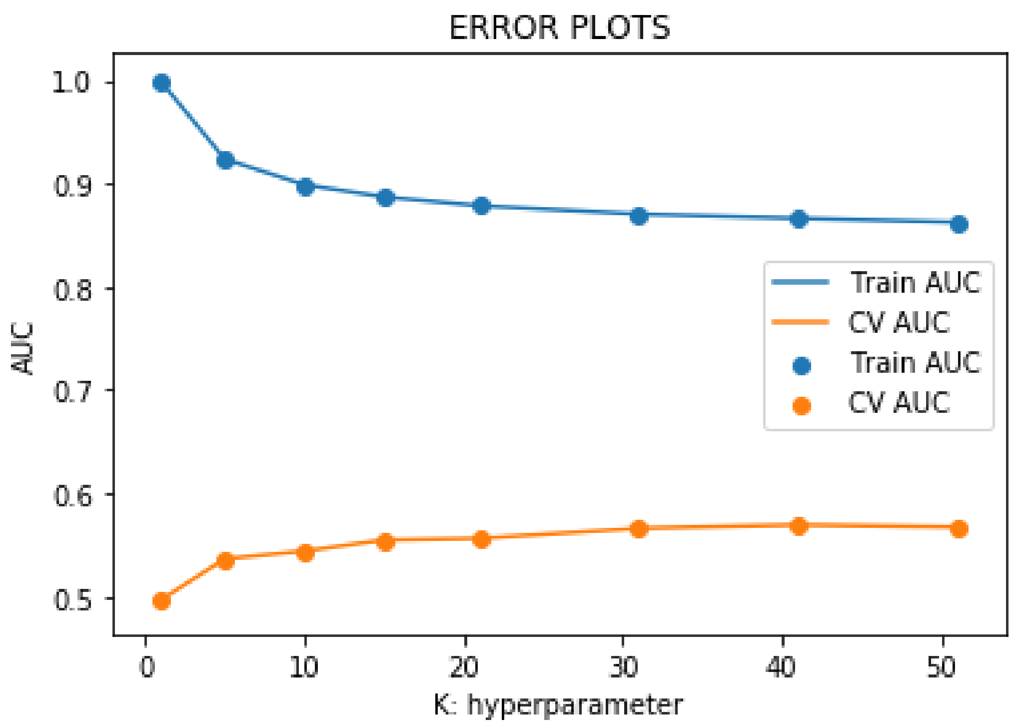

```
==========================================================================================
y_train class counts
1    17598
0     3516
Name: Score, dtype: int64
y_test class counts
1    6693
0    1497
Name: Score, dtype: int64
Train confusion matrix
[[ 1012  2504]
 [  261 17337]]
Test confusion matrix
[[  79 1418]
 [ 257 6436]]
```

6.2.4 [5.2.4] Applying KNN kd-tree on TFIDF W2V, SET 4

In [104]:
```
#It was run with 50k data points
X_train_w2vTfIdf = computeTfIdfW2v(X_train)
X_cv_w2vTfIdf = computeTfIdfW2v(X_cv)

print(type(X_train_w2vTfIdf))
```

```
print(type(X_cv_w2vTfIdf))

findBestK(X_train_w2vTfIdf, y_train, X_cv_w2vTfIdf, y_cv, K, 'kd_tree')
```

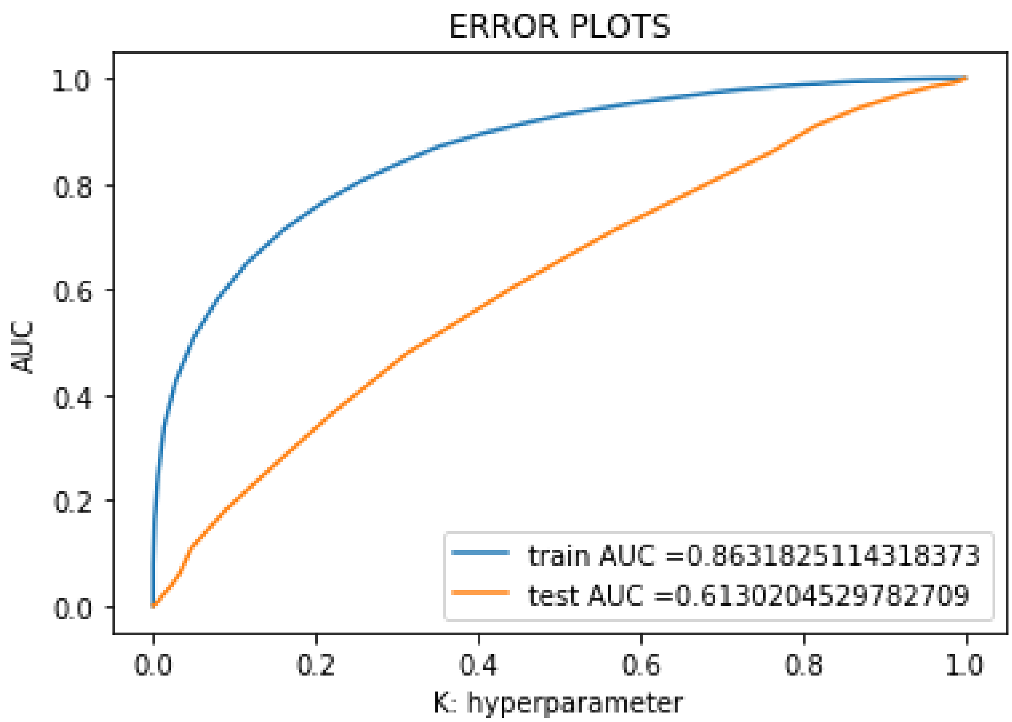
```
100%|| 21114/21114 [03:05<00:00, 113.84it/s]
100%|| 6306/6306 [00:18<00:00, 348.85it/s]
  0%|          | 0/8 [00:00<?, ?it/s]

<class 'list'>
<class 'list'>


100%|| 8/8 [08:33<00:00, 67.59s/it]
```




```
In [107]: #bestK is at 50 based on CV data
          bestk = 50
          X_test_w2vTfIdf = computeTfIdfW2v(X_test)
          print(type(X_test_w2vTfIdf))

          computeWithBestK(bestk, X_train_w2vTfIdf, y_train, X_test_w2vTfIdf, y_test, 'kd_tree
```

```
100%|| 8190/8190 [00:25<00:00, 316.35it/s]
```

```
<class 'list'>
```




```
================================================================================================
y_train class counts
1    17598
0     3516
Name: Score, dtype: int64
y_test class counts
1    6693
0    1497
Name: Score, dtype: int64
Train confusion matrix
[[  706  2810]
 [  201 17397]]
Test confusion matrix
[[   1 1496]
 [   0 6693]]
```

In [3]:
```
import sys
!{sys.executable} -m pip install PTable
```

```
Collecting PTable
  Downloading https://files.pythonhosted.org/packages/ab/b3/b54301811173ca94119eb474634f120a49
```

```
Building wheels for collected packages: PTable
  Running setup.py bdist_wheel for PTable ... done
  Stored in directory: /Users/VJAYANTI/Library/Caches/pip/wheels/22/cc/2e/55980bfe86393df3e989
Successfully built PTable
Installing collected packages: PTable
Successfully installed PTable-0.9.2
You are using pip version 9.0.1, however version 19.1.1 is available.You should consider upgra
```

7 [6] Conclusions

HyperParameter : 1. Tried to find best K using the following K values : K = [1, 5, 10, 15, 21, 31, 41, 51]

Parameter(s) : 0. Tried to do a TimeSeries Train, CV, Test split by querying in Descending Time Order and swapping the train and test output's in call to train_test_split() method. This was based on what was mentioned in the lectures, that product reviews could change over time. And the data span was quiet large where oldest reviews were 20 years old. So i decided to discard old data.

1. The min_count/min_dif threshold parameter was set to 1 for BOW vectorizer but was set to 10 for TFIDF and 5 for W2V. This was to ignore terms that have a document frequency strictly lower than the given threshold, thereby reducing the number of features and computation time (to an extent).

2. Had to reduce the number of samples with KD Tree algorithm as the KD construction was time consuming. When tried with 150K samples, the BOW KD-Tree would not complete one iteration even after 45 minutes.

Results : 1. Results are in the table below

```
In [10]: from prettytable import PrettyTable

         x = PrettyTable()
         x.field_names = ["Vectorizer", "Algorithm", "HyperParameter", "AUC", "DataSize", "Avg
         x.add_row(["BOW", "Brute", 10, 0.66, "150k", 262.96, 1])
         x.add_row(["TFIDF", "Brute", 10, 0.509, "150k", 296.50, 10])
         x.add_row(["W2VAVG", "Brute", 50, 0.739, "150k", 128.20, 5])
         x.add_row(["W2VTFIDF", "Brute", 50, 0.733, "150k", 133.55, 5])
         x.add_row(["BOW", "kd_tree", 50, 0.66, "10k", 91.88, 1])
         x.add_row(["TFIDF", "kd_tree", 50, 0.509, "10k", 94.22, 10])
         x.add_row(["W2VAVG", "kd_tree", 31, 0.62, "50k", 77.69, 5])
         x.add_row(["W2VTFIDF", "kd_tree", 50, 0.61, "50k", 67.59, 5])

         print("Tabular Results:")
         print()
         print()
         print(x)
```

Tabular Results:

Vectorizer	Algorithm	HyperParameter	AUC	DataSize	AvgSecsPerIteration	min_count
BOW	Brute	10	0.66	150k	262.96	1
TFIDF	Brute	10	0.509	150k	296.5	10
W2VAVG	Brute	50	0.739	150k	128.2	5
W2VTFIDF	Brute	50	0.733	150k	133.55	5
BOW	kd_tree	50	0.66	10k	91.88	1
TFIDF	kd_tree	50	0.509	10k	94.22	10
W2VAVG	kd_tree	31	0.62	50k	77.69	5
W2VTFIDF	kd_tree	50	0.61	50k	67.59	5

Observations : 1. The AUC for W2V based Vectorizer seem to be better than corresponding BOW and TFIDF Vectorizer results for both Brute and kd_tree algorithms. 2. The Average Time taken per iteration also seems to be better for W2V. 3. For Brute force TFIDF its not clear why the model perfomed like an AverageModel even when trained with 150k points. One Likely reason is the use of min_df=10 which resulted in a drop in number of -ve samples in y_test as seen in the confusion matrix for TFIDF-Brute (TN=22, FP=55) even though the original y_test had many more -ve samples.